GENERATING CLASSIFIER FOR THE ACUTE ABDOMINAL PAIN DIAGNOSIS PROBLEM

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Abstract- **The inductive learning algorithms are the very attractive methods generating hierarchical classifiers. They generate the hypothesis of the target concept on the base of the set of labeled examples. This paper presents some of the rule generation methods, their usefulness for the rule-base classifier and their quality of classification for the medical decision problem.**
Keywords - **Machine learning, inductive learning, decision tree**

I. INTRODUCTION

Machine learning [1] is the attractive approach for building decision support systems. For this type of software, the key-role plays the quality of the knowledge base. In many cases we can find following problem:

- the experts can not formulate the rules for decision problem, because they might not have the knowledge needed to develop effective algorithms (e.g. human face recognition from images),
- we want discover the rules in the large databases (data mining) e.g. to analyze outcomes of medical treatments from patient databases; this situation is typical for designing telemedical decision support system, which knowledge base is generated on the base on the large number hospital databases,
- program has to dynamically adapt to changing condition.

Those situations are typical for the medical knowledge. For many cases the physician can not formulate the rules, whose are used to make decision or the formulated rule is incomplete.

In the paper we compare the heuristic classifier (given by experts) and three another generated by the chosen inductive learning methods.

The content of the work is as follows. Section 2 introduces idea of the inductive decision tree algorithms and learning sets of rules method. In Section 3 we describe mathematical model of the acute abdominal pain decision problem. Next section presents results of the experimental investigations of the algorithms. Section 4 concludes the paper.

II. ALGORITHMS

We chose three of the inductive learning algorithm.
- C4.5 algorithm given by R. J. Quinlan [3,4],
- Fuzzy Decision Tree Algorithm FID 3.0 given by C. Janikow [3],
- Rule generation algorithm - AQ given by R. Michalski [5].

Inductive decision tree
Algorithms C4.5 and FID are the modifications of ID3 method generating decision tree. Therefore let us present the main idea of the ID3 below

```
Create a Root node for tree

IF all examples are positive
      THEN return the single node tree
Root with label yes and return.

IF all examples are negative
      THEN return the single node tree
Root with label no and return.

IF set of attributes is empty
      THEN return the single node tree
      Root with label = most common value
      of label in the set of examples and
      return

Choose "the best" attribute A from the
set of attributes.

FOR EACH possible value vi of attribute
      1. Add new tree branch bellow Root,
         corresponding to the test A=vi.
      2. Let Evi be the subset of set of
         examples that has value vi for
         A.
      3. IF Evi is empty
            THEN bellow this new branches
            add a leaf node with label =
            most common value of label in
            the set of examples
            ELSE below this new branch
            add new subtree and do this
            function recursive.
END

RETURN Root
```

The central choice in the ID3 algorithm is selecting "the best" attribute (which attribute to test at each node in the tree). The proposed algorithm uses the information gain that measures how well the given attribute separates the training examples according to the target classification. This measure based on the Shanon's entropy of set *S:*

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Abstract

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$$Entropy(S) = \sum_{i=1}^{M} - p_i \log_2 p_i , \qquad (1)$$

where p_i is the proportin of S belonging to klas i $(i \in \mathbf{M}, \mathbf{M} = \{1, 2, ..., M\})$.

The information gain of an attribute A relative to the collection of examples S, is defined as

$$Gain(S, A) = Entropy(S) - \sum_{c \in values(A)} \frac{|S_v|}{|S|} Entropy(S_v), (2)$$

where $values(A)$ is the set of all possible values for attribute A and S_v is the subset of S for which $A = v$.

The C4.5 algorithm modifies ID3 that at the beginning the tree generation procedure does not use the whole set of examples. The FID algorithm assumes that attribute values are the fuzzy observations.

Learning set of rules
The algorithms like CN2 [1] or AQ [5] based on the learning one rule (LOR) strategy, removing data it covers, then iterating the process. This sequential covering procedure is presented bellow.

```
Sequential_covering(examples)
R:= ∅.
P:= examples.
DO WHILE P<> ∅
    r:= learn-one-rule (examples, P).
    R:=R∪r.
    remove from P all examples
    covered by r
END.
RETURN R.
```

The LOR method is similar to the ID3 algorithm presented above. The LOR algorithms follow only the most promising branch in the tree at the each step – returns only one rule, which covers at least some of the examples.
We have presented only idea of algorithm. Of course the method, we talk over, are more complicated. For example we do not present pruning methods whose protect us against situation, where the tree overfits the training set [1, 3, 8].

III. MODEL OF ACUTE ABDOMINAL PAIN DIAGNOSIS
The mathematical model of the diagnosis of acute abdominal pain (AAP) was simplified. Hover the experts from the Clinic of Surgery, Wroclaw Medical Academy, regarded that stated problem of diagnosis as very useful.
It leads to the following classification of the AAP:
1. appendicitis,
2. divercitulitis,
3. small-bowel obstruction,
4. perforated peptic ulcer,

5. cholecystitis,
6. pancreatitis,
7. non-specyfic abdominal pain,
8. rare disorders of "acute abdominal".

Although the set of symptoms necessary to correctly assess the existing APP is pretty wide, in practice for the diagnosis, results of 36 (non-continuos) examinations are used, whose are presented in table I.

TABLE I
CLINICAL FEATURES CONSIDERED

no	feature	no	feature	no	feature
1	sex	13	appetite	25	systolic blood pressure
2	age	14	bowels	26	diastolic blood pressure
3	site on onset	15	micturition	27	movement (of abdomen)
4	site on present	16	previous indigestion	28	distension
5	intensity	17	jaundice	29	tenderness (site)
6	aggravating factors	18	previous similar pain	30	Blumberg's sign
7	relieving factors	19	previous surgery (abdominal)	31	guarding
8	progress	20	drugs	32	rigidity
9	duration	21	mood	33	swellings
10	character on onset	22	color	34	Murphy's sign
11	character on present	23	temperature	35	abdominal auscultation (bowel sounds)
12	nausea and vomiting	24	pulse	36	rectal examinations

Heuristic decision tree
The experts-physicians gave the decision tree [4] depicted on Fig.1. Numbers of leafs are the numbers of diagnosis presented above. The numbers in the nodes are corresponded with the following diagnosis:
9. acute enteropathy,
10. acute disorders of the digestive system,
11. others.

IV. EXPERIMENTAL INVESTIGATION
The presented algorithms C4.5, FID and AQ were used for creating rules for APP decision problem. Their frequencies of correct classification were compared with quality of heuristic classifier [9, 10].
The set of data has been gathered in the Surgery Clinic. It contains 476 learning examples.
For each learning method the following experiment was made:
• from the learning set 40 examples was chosen (according with frequency of the class appearance); this set was use for test,
• the rest of examples (436) were training ones.
This procedure was repeated 20 times for each of the algorithms. The results of the experiments are presented in Table II and depicted on Fig.2.
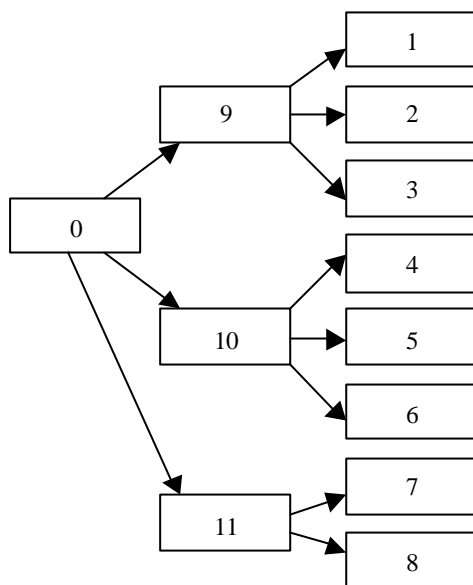
Fig. 1. Heuristic classifier for the APP diagnosis problem

TABLE II
FREQUENCY OF CORRECT CLASSIFICATION

Class number	Heuristic	AQ	C4.5	FID
1	79,1	90,5	95,8	86,7
2	88,2	55,0	92,3	100
3	93,1	95,0	95,8	100
4	67,1	90,0	95,6	66,7
5	82,5	98,8	86,9	83,3
6	84,4	85,0	96,2	75,0
7	84,7	97,5	91.5	75,0
8	88,2	75,0	92,3	50,0
average	83,0	85,8	93,3	80,4

The results of test are clear. The classifier given by C4.5 algorithm is always better than heuristic one. The AQ and FID algorithm gives the better results for some of class, but for another the frequency of correct classification is very low. Experts revised the structures of classifiers given by inductive learning algorithms. They confirmed that all of rules were correct and maybe the heuristic classifier was incomplete.

V. CONCLUSION

The methods of inductive learning were presented. The classifiers generated by those algorithms were applied to the medical decision problem (recognition of Acute Abdominal Pain). The results of test were compared with recognition quality of heuristic algorithm.

It must be emphasised that we have not proposed a method of "computer diagnosis". What we have proposed are the algorithms whose can be used to help the clinician to make his own diagnosis. The superiority of the presented empirical results for the inductive learning classifiers over heuristic one demonstrates the effectiveness of the proposed concept in such computer-aided medical diagnosis problems. Advantages of the proposed methods make it attractive for a wide range of applications in medicine, which might significantly improve the quality of the care that the clinician can give to his patient.

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